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Strategic Online-Banking Adoption *

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Abstract

In this paper we study the determinants of banks' decision to adopt a transactional website for their customers. Using a panel of commercial banks in the United States for the period 2003-2006, we show that although bank-specific characteristics are important determinants of banks' adoption decisions, competition also plays a prominent role. The extent of competition is related to the geographical overlap of banks in different markets and their relative market share in terms of deposits. In particular, banks adopt earlier in markets where their competitors have already adopted. In order to construct the different local markets, this paper is one of the first that makes use of the geographic market definitions delimited by the Cassidi® Database compiled at the Federal Reserve Bank of St. Louis.

JEL Codes: O31, G21, L10, C41.
Keywords: Duration Models, Technological Adoption, Online Banking, Competition.

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1 Introduction

The arrival of the Internet not only spurred the development of new industries but it also changed the business model of many others. This is, for example, the case of the banking sector. In 1995, the Security First Network Bank was the first internet-only bank created. Around the same time, Wells Fargo was the first brick-and-mortar bank to establish its online presence. For most of the rest of the banks, however, online presence in the first few years simply meant only the creation of a static corporate website. Banks soon started to develop software applications that first allowed customers to access their accounts and later allowed them to perform financial operations online. By the end of 2003, more than half of the commercial banks present in the U.S. offered some *online-banking* services to their customers.

The purpose of this paper is to analyze the determinants of a bank's decision to adopt online banking. In particular, we focus on the strategic considerations of this adoption, mainly in response to the adoption decisions of competitors in the same markets. We show that banks that operate in markets where competitors have already adopted online banking tend to adopt earlier. This effect persists even after controlling for the standard measures of the degree of competition in the market and other market characteristics. Bank specific measures, such as its size, as well as standard measures of a bank's financial health are also important determinants.

There is a considerable literature, particularly in the field of industrial organization, regarding the optimal adoption of new technologies by a firm. For example, Oster (1982) studies the introduction of the basic oxygen furnace used in steel making. She approaches this decision as technologically driven, independent of the decisions taken by competitors.[1] Later papers have introduced strategic considerations, mainly through the use of the Herfindahl index as a summary statistic of the intensity of competition. In the banking industry this strategic component is studied in Hannan and McDowell (1984) and Hannan and McDowell (1987) in the adoption of ATMs, and in Akhavein et al. (2005) for the adoption of credit scoring.[2]

Karshenas and Stoneman (1993) summarizes the determinants of the decisions to adopt a new technology in a competitive context.[3] These determinants are structured around 4 different mechanisms: *rank*, *stock*, *order* and *epidemic effects*. Rank effects, mainly related to firm *size*, stem from the fact that adoption costs typically increase less than proportionally with the size

[1]Rose and Joskow (1990) study adoption decisions in markets where firms are local monopolies. In this case, the assumption that strategic interactions are absent is rather natural.

[2]Also in the context of ATMs, Saloner and Shepard (1995) and Gowrisankaran and Stavins (2004) study the network effects that technology adoption entails. Pennings and Harianto (1992) study the effect of the information technology accumulation in banks and the linkage across institutions in the adoption of videobanking.

[3]See Geroski (2000) and Hoppe (2002) for a review of the theoretical literature.

of the firm and decrease over time. As a result, firms adopt according to their size: larger firms adopt earlier. Stock effects are related to the idea that the benefits from adopting a new technology depend strategically on the *number* of firms that have already adopted it. Order effects arise when the return from adoption depends on the *order* in which firms have adopted, for example, due to preemption motives: firms might adopt early to make adoption unprofitable to competitors. Finally, epidemic effects assume that the *diffusion* of new technologies is faster when more firms have adopted.

The decision to provide online-banking services is different from the replacement of an existing technology studied in the classical examples in the adoption literature. Instead, online banking coexists with the traditional channels that include not only bank branches but also telephone banking. For example, opening an account requires a visit to the branch, and this is also (together with ATMs) the main way to withdraw or deposit money. At the same time, online banking reduces the cost of providing a wide variety of products to customers. Whether different channels substitute or complement each other is an empirical question. Corrocher (2006) for example, finds for Italy that online-banking and physical presence (measured as branching intensity) are substitutes. An interpretation is that, for less established banks (with fewer branches) online-banking is a more efficient way to access new clients. DeYoung et al. (2007) in a sample of U.S. banks in the late 1990s, however, finds that branching intensity and online banking are complementary and also shows that online-banking adoption positively affects the bank's later performance.[4]

In spite of the importance of online banking, the literature on its adoption is still scarce. Very few papers have studied the demand for these services. One example is Chang (2004) which studies the consumer-adoption decision of this technology in South Korea. The author infers that risk aversion and customer inertia make bank investments in this new technology unlikely to be profitable. As a result, she concludes that bank adoption might arise due to the positive reputation effects it entails or preemptive motivations towards competitors.

Studies regarding the supply side for the U.S. include Furst et al. (2001), Nickerson and Sullivan (2003) and Sullivan and Wang (2005). Furst et al. (2001) studies the determinants of adoption using a cross-section of banks for 1999. The authors do not include strategic considerations. They show that profitability, bank size, presence in urban markets, and membership in a bank holding company are all positive and good predictors of the decision to adopt.

Nickerson and Sullivan (2003) embeds the strategic decision regarding the adoption of online banking in a real options environment. Their theoretical model shows that market leaders are more

[4]This divide has also arisen in the study of the adoption of ATMs in relation to the number of branches. Whereas Ingham and Thompson (1993) finds that ATMs and physical branches are substitutes, Saloner and Shepard (1995) obtains the opposite result.

likely to adopt if competition consists of small firms or if uncertainty in the demand is small. They confirm these hypotheses using also a cross-section for 1999. Sullivan and Wang (2005) studies the pattern of diffusion of technological innovations in different states. They propose a theoretical model that is later tested using observations at the statewide level. They estimate slower adoption patterns for those states where per capita income is lower, internet access is more scarce or banks are older. More important, adoption is also slower in states where banks are smaller. To the extent that rank effects make big banks more likely to adopt, the authors interpret this last result as supportive of the existence of epidemic effects, since smaller banks could learn from them.

Our paper departs from the previous literature in that we measure the strategic decision of firms to adopt online banking as a response to the adoption decisions of competitors. In the terminology introduced earlier, we measure the total stock and order effects. In principle, the increasing adoption of online banking is no indication of a positive effect on the adoption probability of the late adopters, as most of the adoption is likely to be driven by the fast decrease in the cost of providing this service. In principle, two opposing strategic forces might shape the adoption decision. On the one hand, an increasing adoption by competitors reduces the profits from implementing the technology and might delay adoption. On the other hand, the profits from not adopting might be reduced in a larger or smaller extent depending on how important is this additional service to customers. Which force dominates and whether this force operates in a different direction for different kinds of banks is the empirical question we want to address. Overall, our results show that the decline in profits from not adopting dominates, as the banks' adoption probability increases in response to the adoption of competitors.

In order to quantify these effects we use a dataset on online adoption that has been available only recently. Starting in 2003, the Federal Deposit Insurance Corporation (FDIC) asked institutions to indicate in their quarterly *Call Reports* whether their websites allowed customers to execute transactions or not.[5] We complement this dataset with information at the bank level using the Summary of Deposits also from the FDIC, and demand characteristics obtained from the U.S. Census Bureau. As opposed to other papers in the literature, we benefit from the construction of a panel that allows us to estimate a hazard model of the time until the adoption decision.

To the extent that we are interested in determining the strategic component of adoption, it is essential to identify the relevant market in which banks operate, and the competitors they face. Unfortunately, there is no obvious way to delimit this competition. Many banks compete at a national level, others at the state level, and finally, many small banks are local. For this reason, in order to isolate the effect of online presence we adapt the concept of *Multimarket Contact* used

[5] Call Reports also track the presence of an internet website since 1999.

in papers such as Evans and Kessides (1994) for the airline industry. The idea of this index is to weigh the characteristics of each competitor according to how close a substitute their product is. In the case of the banking industry, two banks can be considered closer substitutes if, among other things, their network of branches overlaps more often. In the sample and period we analyze, a large majority of the banks that have not adopted Internet banking are small and operate in local markets for which competition is still geographically localized and whose clientele is for the most part formed by retail depositors and small business borrowers.

Our index of Multimarket Contact is constructed as a weighted sum of indicator functions for a bank's competitors at the local-market level. The indicator is 1 if the competitor has adopted online-banking and its weight corresponds to the share of the deposits that the competitor holds in this market. The Multimarket Contact index averages the values for the different markets according to the share of the total deposits of the bank that each market represents. Obviously, this index is bank specific and it varies over time.

In this paper we use the Multimarket Contact index (MMC) to address different issues from the ones studied in the literature. While papers such as Evans and Kessides (1994) and Waldfogel and Wulf (2006) relate the extent of multimarket contact with the probability that firms tacitly collude, in this paper we take this index as a proxy of the strategic motivation for banks to adopt online operations as a competitive response to the rivals' actions.

The definition of the relevant market is a controversial issue both in the literature and as part of the decisions of regulators and antitrust authorities over proposed mergers. Kwast et al. (1997) estimated that, in 1992, more than 75% of households and small businesses did their banking business within 15 miles of their house/work and offices, respectively. In recent years, for some products bank competition is becoming global. Petersen and Rajan (2002) show, for example, that the increase in hard information on the credit activity of small firms has reduced the advantage of the local presence of banks in lending activity. For some other products, however, competition is still geographically localized. Heitfield and Prager (2004) shows that this is the case for checking accounts and to a lower extent for saving accounts and money market deposit accounts.

The market definitions we use in this study constitute another contribution of this paper. We use market definitions from the recently available Cassidi® database, compiled by the Federal Reserve Bank of St. Louis. These market definitions by the twelve Federal Reserve districts have arisen mostly in response to antitrust disputes resulting from mergers and acquisitions. To the best of our knowledge, ours is the first paper to make use of the Cassidi® definitions.

In addition to the competitive environment, we also analyze which firm-specific factors constitute the most important determinants in the decision to adopt online banking. We find that firm characteristics such as size or belonging to a holding company positively affect the decision to adopt. Indicators of a bank's financial health and business strategy such as the loans to assets ratio and the share of nonperforming loans are also found to be important factors in the adoption decision. We also contribute to the debate over the substitutability or complementarity of online banking and other channels of bank presence, as measured by branching intensity or the ratio of the number of branches to assets. We find evidence of substitutability, since banks with greater branching intensity tend to delay adoption.

Controlling for these bank-specific characteristics, our results support the hypothesis that competitive considerations play an important role in adoption decisions. We find that controlling for the concentration in deposits (as measured by the Herfindahl index) facing banks in the various markets in which they operate, the MMC index allows us to conclude that for similar levels of concentration in the market, adoption of online banking occurs faster in markets where rivals have already adopted.

Our results shed some light on which of the determinants described by Karshenas and Stoneman (1993) underlie the adoption decisions of online banking. Rank (size) effects are the main motivation. Although epidemic effects could have been important in the initial days of online banking, we find that after the technology has been established they have not had a significant impact, at least in the diffusion among firms in the same holding group. The significant coefficient for the MMC indicates that competition also plays an important role. In other words, a bank's adoption is partially triggered by the competitors' adoption. Furthermore, the positive effect of competition on the decision to adopt rules out predominant order (or preemption) effects, that would be consistent with a negative sign of the MMC. Our results, therefore, are in line with a positive impact of stock effects. Banks that are yet to adopt could be affected by a *stigma* vis-a-vis its competitors.

Our estimations are robust to changes in the measures of the relevant market definition or the variable used to denote the online presence. In particular, using alternative market definitions, such as local markets at a zip code or county level, also yields a positive relationship between the competitors' adoption (measured by the MMC index) and a bank's adoption decision.

We also address the possible simultaneity of our measure of multimarket contact in the sense that it could be caused by market-specific characteristics that might at the same time be causing the individual bank adoption. Accounting for this possibility with a two-stage logit procedure yields no evidence of such an effect.

Finally, we study whether a bank's decision to adopt is taken individually or at the holding company level. Our first look at this issue shows that not all banks in a group adopt simultaneously. This evidence suggests that although a bank's cost to adopt decreases when other banks in the holding company have already adopted, overall, the online banking adoption decision is better explained as a bank-level choice.

Section 2 briefly describes the sector and the evolution of online banking adoption in the United States. Section 3 discusses the measures of competition used in the paper. Section 4 presents the empirical strategy. Section 4 explains the construction of the database and section 5 discusses the main specification. Section 6 performs some robustness checks and section 7 concludes.

2 The Pattern of Online-Banking Adoption

Customers interact with their banks in several ways. Although most of the transactions traditionally occurred at the branch counter, new technologies have reduced the costs that customers had to bear. For example, ATMs became widespread by the mid-eighties, making some transactions easier. Telephone banking, initially human operated and later voice automated, reduced the need to visit a bank's physical branch. In recent years, particularly since 1995, the internet has made banking easier and allowed institutions to offer newer services to their customers, further reducing the need to stop by a branch office.

The cost of setting up a transactional website has decreased substantially in recent years, making the significant cost savings it entails very profitable. Good estimates of the cost of setting up a transactional website are difficult to come by. Celent, a financial consulting company, estimated that in 2000 the cost of building an in-house online banking system exceeded $500,000, although the costs of outsourcing it were substantially smaller.[6] This last option should be more attractive for smaller banks like the ones present in our sample. Our econometric specification will capture the cost of online banking as part of the time trend. Regarding marginal costs, the cost of an online transaction is estimated to be as low as $0.01 as opposed to the cost of a transaction at a branch of $1.[7] These cost savings together with the widespread use of the internet has enticed smaller banks to adopt this technology. According to DeYoung (2001) around 1,100 banks and thrifts operated a transactional website in 1999. This number increased to around 4,000 banks at the beginning of 2003. Since then, banks have adopted at a rate of about 5% per quarter. By the end of 2006 around 6,600 banks (80% of the total) provided online banking to their customers. Figure 1 shows the evolution of adoption in recent years.

For the purpose of this paper, it is important to emphasize that internet-only banks (those that operate without any branch) have remained an oddity in the United States. In 2000 they accounted for less than 1% of the deposits and constituted less than 5% of all transactional websites. In 2004,

[6] See http://www.aba.com/NR/rdonlyres/04DAD6EC-0908-11D5-AB75-00508B95258D/12952/Is_Internet_Banking_Profitable999998.pdf.

[7] See The Economist (2000) and the references therein.

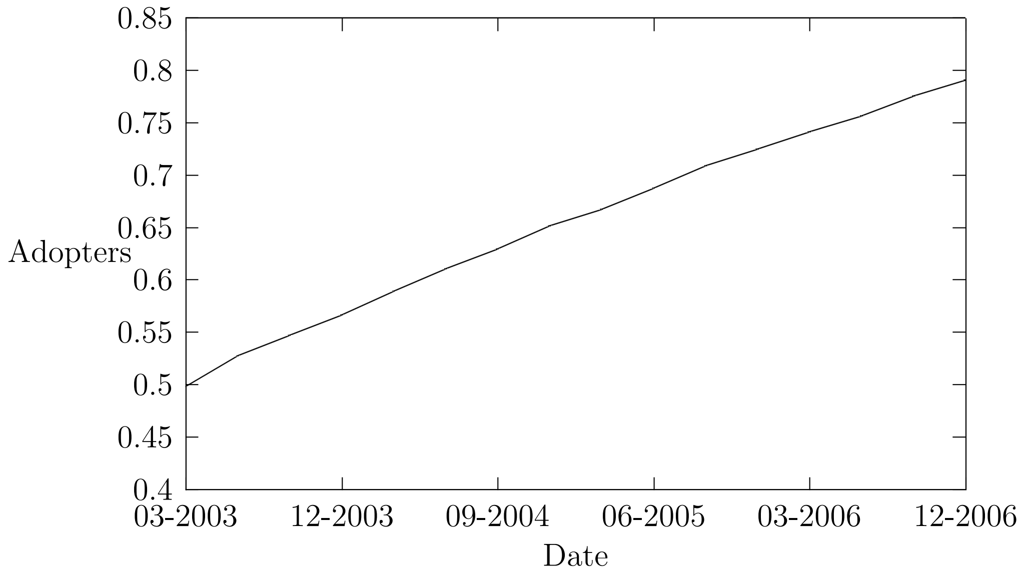

Figure 1: Proportion of banks that have adopted online-banking in the period 2003-2006.

there were less than 30 internet-only banks.[8] In fact, entry through the creation of bank branches has remained important, and over 40% of the entrants during our sample period did not initially provide a transactional website.

Table 7 in the appendix shows the stark differences between those banks that adopted prior to the beginning of 2003 and those that were yet to adopt. Non-adopters were in general smaller in terms of deposits (and total assets) and had on average 80% fewer branches. They also operated in fewer markets and devoted a bigger proportion of their activities to non-urban markets.

The larger size of earlier adopters, consistent with the rank effects previously mentioned, is natural for several reasons. The main one, as mentioned above, is that the setup cost of online services is not likely to be sensitive to the size of the bank. Beyond that, smaller banks face additional challenges. For example, Nathan (1999) emphasizes that community banks (usually defined as banks with total assets of $1 billion or less) rely more for customer screening on closer and more personalized contact. For them, the access to a wider market, and more difficult to monitor, might be less profitable.

[8]See DeYoung (2001) and Wang (2006). The last author argues that their little success is due to the complementarity between brick-and-mortar and online channels: While standardized products are easily distributed through the online channel, specialized products require a branch presence. As a result, internet-only banks are found to have on average a lower return on assets. Delgado et al. (2004) finds similar evidence for European banks attributed, however, to the lack of economies of scale derived from their smaller size.

3 Measures of Competition

3.1 The Index of Multimarket Contact

This paper originates from the idea that the decision to adopt online banking depends on the behavior of competitors over and above the level of market concentration previously considered in the literature. In the banking industry, expanding the number of branches and choosing their location has traditionally constituted one of the main channels of competition. Online banking provides an alternative strategy to the creation of new bank branches, while at the same time it reduces customer transaction costs.

At least in the short run, the provision of online banking services is likely to steal customers from competitors that operate in similar geographic areas, where overlapping of their branch network is important. The Multimarket Contact Index (MMC) accounts for this factor by giving different weights to banks that coincide in different areas and have a different volume of deposits. In particular, if bank i has branches in the set M_i of markets and we denote as B_s the set of banks that operate in market s, we compute the MMC as

$$MMC_i = \sum_{s \in M_i} \frac{D_{is}}{\sum_{r \in M_i} D_{ir}} \times \sum_{j \in B_s \setminus \{i\}} I_j \frac{D_{js}}{\sum_{k \in B_s \setminus \{i\}} D_{ks}},$$

where D_{js} denotes the sum of deposits of bank j in market s and I_j is an indicator function that takes the value 1 if bank j has adopted online banking in a previous period and 0 otherwise.[9] Notice that the index excludes the bank for which it is computed. This exclusion avoids some spurious correlation in our estimations originating from the period in which the bank decides to adopt and the corresponding change in multimarket contact.

This index can also be interpreted as the share of deposits controlled by the competitors of bank i that have already adopted in the markets where this bank operates. The weights assigned to each competitor are increasing in its market share in that particular market. These weights are also increasing in the share that this market represents in the total volume of deposits of bank i.

Figure 2 shows the MMC index for banks that had not adopted by the first quarter of 2003. In most of the markets where these banks operate a vast majority of competitors have already adopted. As a result, we could expect banks in our sample to be factoring in their adoption decision a response to the rivals' adoption.

During the sample period under study, 59% of the banks that had not adopted by the first quarter of 2003 had adopted by the fourth quarter of 2006. The pattern of adoption, however, was

[9]This index is bank- and period-specific. However, in order to simplify the exposition we have excluded the time subscript in the formulas.

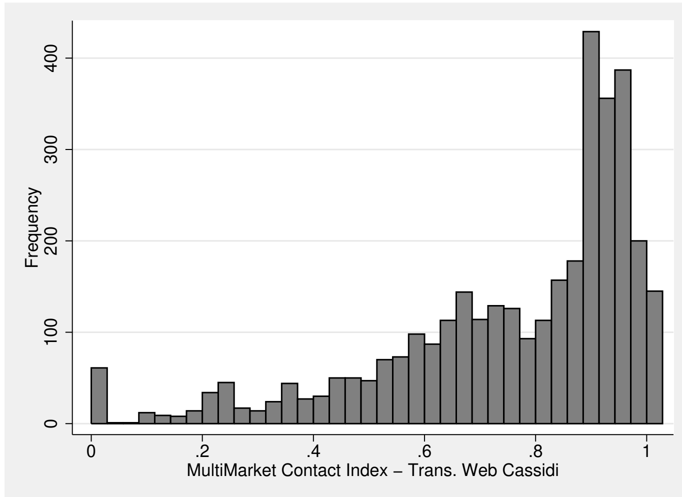

Figure 2: The MMC index for the first quarter of 2003 among all banks that had not adopted.

	$MMC < 0.2$	$MMC > 0.8$
Adoption (I=1)	43(44%)	1475(62%)
No Adoption (I=0)	55(56%)	914(38%)

Table 1: Adoption in the period 2003-2006 for different values of the initial 2003 MMC.

different for those banks that operated in markets where competitors have already adopted and those that were yet to adopt. As Table 1 shows, adoption in markets where the MMC was close to 1 in 2003 was, on average, almost fifty percent more likely than in those markets where the MMC was close to 0.

3.2 The Herfindahl-Hirschman Index

The adoption decision by competitors is not necessarily the only strategic consideration in a bank's decision to adopt online banking. The literature discussed in the introduction has already provided substantial evidence showing that adoption depends on the characteristics of the markets in which each bank operates. Besides demand-side considerations that are likely to influence the profitability of online banking (consumer internet access, education attainment, level of income, etc), this profitability is likely to depend also on the level of competition in each market. Some standard theories, for example, suggest that competition spurs innovation as a way to achieve cost reductions or to achieve differentiated products.

In this paper, we measure competition using the Herfindahl-Hirschman Index (HHI). As opposed to the usual analysis of competition among firms that operate in the same market, different banks have activities in different geographical areas. As a result, the measures of competition will be also bank-specific, reflecting the average conditions among all the markets in which each bank operates. For this reason we compute the HHI for bank i as the weighted average of all the HHIs in the local markets where this bank operates. Similarly to the MMC computed earlier, the weights correspond to the share of total deposits of bank i in each of the markets. In particular, the formula is given by

$$HHI_i = \sum_{s \in M_i} \frac{D_{is}}{\sum_{r \in M_i} D_{ir}} \times \sum_{j \in B_s} \left(\frac{D_{js}}{\sum_{k \in B_s} D_{ks}} \right)^2 .$$

An important concern, however, is that online banking changes the nature of bank competition, making geographical location of bank branches irrelevant. This change should have a limited impact on our results. First, banks of similar size are likely to be exposed to similar increases in competition due to the adoption of other institutions, adding to the constant term of our regressions. Second, as mentioned before, customers of small banks (like the ones in our sample) typically place an important value to the personalized service, which emphasizes the local component.

4 The Empirical Model

In the empirical model we estimate the determinants of the timing of adoption. This decision is intrinsically dynamic in nature. When a bank decides whether to adopt in a particular moment in time or not, it compares the cost to be incurred and the increase in present value of profits with what could be attained in the best alternative time of future adoption. This decision is in essence an optimal stopping-time rule.

We denote the present value of profits of firm i (net of the cost of adoption) when it adopts in period t as V_{it}^A. Similarly, we denote the present value of profits of not adopting in t, and instead waiting until the best future period, as V_{it}^{NA}. We posit a reduced-form model for the difference in profits between these two options as a latent variable y_{it}^* which depends on a vector of exogenous variables affecting the adoption decision as follows

$$y_{it}^* = \alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it} + \varepsilon_{it}.$$

The vector of variables x_{it} corresponds to bank-specific characteristics, w_{it} are market characteristics, z_{it} are measures of competition, and ε_{it} is an error term.[10] Notice that in our specification

[10]These regressors can be interpreted as the relevant state variables in the dynamic problem.

both market characteristics and measures of competition are bank-specific, since they are weighted according to the deposits of each bank across all the geographical markets where it operates.

We do not observe the latent variable y_{it}^{*} and instead we observe the outcome of the adoption decision, y_{it}. We define this variable to be equal to 1 if the firm i offers online-banking services and 0 if it has not adopted them yet. We assume that a bank adopts in period t if and only if its present value of profits of adopting is higher than the present value of profits of waiting. That is, $y_{it} = 1$ if and only if $y_{it}^{*} = V_{it}^{A} - V_{it}^{NA} \geq 0$. Furthermore, we assume that the adoption decision is irreversible. Thus, banks do not provide (to the econometrician) any additional information after they have adopted.

We estimate a discrete hazard model of duration until the adoption decision. Let T_i be the random-variable representing the period of adoption for each bank i. The hazard rate of adopting in period t, the probability of adoption in period t conditional on not having adopted before, is defined as

$$h_{it} \equiv \Pr\left(T_i = t | T_i \geq t; x_{it}, w_{it}, z_{it}\right).$$

Thus, the unconditional probability of adoption in period t corresponds to

$$\begin{aligned} \Pr\left(T_i = t\right) &= h_{it} \prod_{s=1}^{t-1} \left(1 - h_{is}\right) \\ &= \frac{h_{it}}{1 - h_{it}} \prod_{s=1}^{t} \left(1 - h_{is}\right), \end{aligned}$$

and the unconditional probability that the firm adopts at a future date is

$$\Pr\left(T_i > t\right) = \prod_{s=1}^{t} \left(1 - h_{is}\right).$$

Building on Allison (1982), papers such as Jenkins (1995) show that this model can be easily estimated using the following log-likelihood function:

$$\log \mathcal{L} = \sum_{i=1}^{N} \sum_{t=1}^{S_i} \left[y_{it} \log h_{it} + (1 - y_{it}) \log(1 - h_{it})\right],$$

where S_i is the actual number of periods bank i is present in the sample. This is the likelihood function of a static discrete-choice model for y_{it} that can be estimated using standard econometric packages. However, it is particular in the way in which observations are organized. The model stacks all the observations for a particular bank for all the periods before it adopts, and it drops observations of that bank in all periods after adoption since they do not provide additional information regarding this decision.[11]

For the purpose of this paper we use a logit specification for this discrete-choice model, which in this case implies that

$$h_{it} = \frac{\exp\left(\alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it}\right)}{1 + \exp\left(\alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it}\right)}.$$

5 Data

Our dataset consists of quarterly information for all commercial banks in the U.S. during the period 2002:1-2006:4. These data were obtained from the Call Reports made available by the Federal Reserve Bank of Chicago.

Since the second quarter of 1999, the Call Reports provide the address of a bank's website if it exists. Most important for this analysis, starting in the first quarter of 2003, they also report whether the bank's website offers transactional capabilities, such as downloading statements, transferring money between accounts, or paying bills. We use this variable as the indicator for the adoption of online-banking. This variable is also used in the construction of the multimarket contact index.

From the Call Reports data we obtain bank-specific variables used in the vector x_{it}. These variables include: (log) total assets to measure bank size, the number of branches, and the (log) age of the bank. The Call Reports also allow us to construct standard measures of profitability and bank financial health, such as the return on assets, the share of non-performing loans, the loans to assets ratio, and the equity to assets ratio. Following other papers in the literature, we have constructed the variable for branching intensity as a ratio of number of branches over total assets. We have lagged this variable one period in order to avoid endogeneity issues.

We have also gathered annual branch-level data for each bank in the sample using the Summary of Deposits from the FDIC. This dataset includes for each bank the deposits per branch as of June of each year. This dataset provides information about the geographical location of each branch, including the postal address, and whether the branch is located in a metropolitan area or not.

The Summary of Deposits also reports information on whether the bank belongs to a multi-bank holding company, a one-bank holding company or it is an independent bank. We include these variables as additional bank characteristics in the vector x_{it}. We take the indicator for an independent bank as the reference category and we include the other two as dummy variables.

[11] For that same reason we cannot obtain additional information from the firms that adopted before the first period in our sample without very strong assumptions. The reason is that adoption means that the present value of profits was positive at the moment of adoption but it does not imply that they were also positive in the initial period of the sample.

We match the deposits data from the Summary of Deposits with the bank level information from the Call Reports and we use them to construct the measures of competition in the vector z_{it}, i.e., the HHI and MMC indexes discussed earlier in the paper.

Finally, we also control for several market characteristics in the vector w_{it}. First, we account for whether the bank operates in metropolitan or rural areas averaging the share of deposits that corresponds to branches located in metropolitan areas over all of the bank's branches. Second, we obtain demographic information at the county level from the 2000 U.S. Census. These variables include median household income, and the percent of people aged 18 to 64 who have completed a bachelor's degree or higher. We add to this information the percent of households with internet access from the 2003 Internet Usage Supplement of the Current Population Survey.[12] For banks that operate in more than one state, all the demographic variables are averaged across markets using as weights the share of the deposits that each market represents for the bank. Therefore, although the demographic variables are time-invariant, the bank-specific averages do vary over time (on an annual basis) because the deposit information is observed once every year.

Summary statistics of the above variables are presented in Table 7 in the appendix. Table 8 reports the correlation among the variables.

5.1 The Cassidi Markets

The 12 Federal Reserve Banks define local banking markets within their districts. Banking regulators use these definitions, for example, when analyzing mergers or acquisitions. According to the 2006 Annual Report of the Federal Reserve Bank of St. Louis,

> "A local banking market is an economically integrated area that includes and surrounds a central city or large town. Often banking markets are based on metropolitan or similar areas in urban regions, and on counties in rural regions. Local economic and demographic data – such as commuting patterns, locations of large employers and retailers, an other information that could demonstrate an economic tie or separation between two areas – are used to enlarge or shrink the size of the market from the base."

So far around 1,500 markets have been defined according to these criteria, encompassing most of the country. Many of these markets straddle two or more states. The Federal Reserve of

[12] The 2003 Internet Usage Supplement provides, for each state, an estimate of the share of households with internet access at the state level and an estimate of the share of households with internet access for households residing in metropolitan areas. We assigned the metro estimate to all metropolitan counties in the state and we assigned the state estimate to all nonmetropolitan counties in the state.

St. Louis has homogenized this information and made it available at their Cassidi® website.[13] The application created in this website includes all currently defined markets and interactive maps for many of them.

Our initial database consists of observations for 7,788 banks present in the first quarter of 2003. We eliminate 3,683 banks that have already adopted (they already have a transactional website) in the first period of the sample. We also eliminate 2 banks with coding errors in the indicator for online-banking adoption in the first period. The resulting bank panel has 4,103 banks that have not adopted by the first quarter of 2003. Of these banks, 445 do not appear in all periods of the sample, probably as a result of bank failures or acquisitions.[14] For each bank we observe at most 15 quarters until the adoption decision is made, since by construction we do not observe any adoption in the first period. Of these banks, 4,048 were community banks, with assets of strictly less than 1 billion dollars. By the end of the sample there were still 1,599 banks yet to adopt.

We have matched the address of each bank branch with the Cassidi bank market definitions. There is a small fraction of bank branches in cities or towns for which a Cassidi market has not been defined. For these cases, in our benchmark model we substitute the corresponding county or metropolitan area as the market of reference. The benchmark results do not change substantially if we dropped those observations instead.

In the logit regressions, future observations of banks are eliminated from the sample after they decide to adopt. In total, the resulting unbalanced panel has about 42,000 observations. Some additional observations are lost when we construct the instruments we use in the two-stage logit we discuss later in the paper.

6 Results

The results of the baseline estimation are reported in Table 2 for four different specifications. In model (1) we include only bank-specific variables in addition to the multimarket contact index. In model (2) we also include the Herfindahl index to control for market concentration, and in model (5) we control also for demographic variables. Whereas models (1) to (3) include a second-order polynomial for a time trend, model (4) introduces time fixed effects. In what follows, we discuss the average marginal effects presented in the accompanying columns, but qualitatively there are little differences between the 4 models presented. All financial ratios, as well as the MMC index, are measured in decimal points (0.01 is equivalent to 1 percentage point). The HHI is normalized to be

[13]See `http://cassidi.stlouisfed.org`. We specially thank Adam Zaretsky and Neil Wiggins for providing us with the data and helping us understand some of its peculiarities.

[14]Our estimation results do not differ significantly if those banks are excluded from the sample.

between 0 and 1. The demand variables (education, internet access) are measured as percentages. Median household income is measured in thousands of dollars.

The effects of the bank-specific variables are similar across model specifications. The size of the bank in terms of (log) assets has the expected positive effect on the decision to adopt. To the extent that the cost of adoption is quite invariant with the size of the bank, larger banks are likely to adopt earlier.[15] Because assets are measured in logs, the interpretation of the coefficient of 0.01250 (in column 5 of table 2) is that, on average (across all observations) an increase of 5% in assets increases the probability of adoption by approximately 6 basis points per quarter (0.01250 $\times$ 0.05 = 0.000625 or 6.25 bp) and the effect is statistically significant. Membership to either a one-bank or a multi-bank holding company is also positive and statistically significant. Banks in a one-bank holding company are about 2 percentage points more likely to adopt than stand-alone banks, whereas banks in a multi-bank holding company are about 3 percentage points more likely to adopt than stand-alone banks.

A standard measure of banks' overall health, the share of non-performing loans, has a strongly negative and statistically significant effect on the decision to adopt. On average, an increase of 1 percentage points in the share of non-performing loans reduces the probability of adoption by about 50 basis points per quarter. In other words, banks with a worse loan portfolio would tend to delay adoption. This result might be due to short-run considerations derived from concerns related to the survival of the bank as opposed to the long-run investment that online banking represents.[16]

A common measure of profitability is the return on assets. Our results indicate that this variable has a negative and statistically significant effect on the adoption decision. An increase of 1 percentage points in the return on assets decreases the probability of adoption by about 28 basis points per quarter. This result suggests that less profitable banks are hard pressed to adopt online banking sooner, perhaps as a way of exploring new business opportunities in an attempt to improve profitability. Nevertheless, because most of the banks in our sample are small, the usage of return on assets as a measure of profitability in this case is subject to important caveats as exposed in Gilbert and Wheelock (2007). Hence, the interpretation of this measure must be taken with caution.

The probability of adoption is also positively related to the ratio of loans to assets. A 1 percentage point increase in this ratio increases the probability of adoption by about 6 basis points per quarter. One possible interpretation of this result is that more aggressive banks hold a

[15]The time trend in the specifications would then capture, among other things, the common component in the technological progress that drives down the cost of adoption.

[16]Alternatively, it could be argued that to the extent that online banking can be used as a way to capture new customers, banks that are better at screening projects (and have a lower non-performing loans ratio) obtain a higher revenue per customer, and this entices them to adopt earlier.

Table 2: Bank Adoption of a Transactional Website

	Logit Coefficients				Average Marginal Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
time	0.01745	0.01785	0.02050		0.00084	0.00086	0.00099	
	(0.808)	(0.826)	(0.948)		(0.808)	(0.826)	(0.948)	
$time^2$	0.00064	0.00063	0.00063		0.00003	0.00003	0.00003	
	(0.474)	(0.467)	(0.464)		(0.474)	(0.467)	(0.464)	
Branching Intensity	-5.56955	-5.56337	-5.60718	-5.62457	-0.26941	-0.26910	-0.27089	-0.27131
	(4.736)***	(4.731)***	(4.736)***	(4.746)***	(4.720)***	(4.715)***	(4.720)***	(4.730)***
Loans to Assets Ratio	1.40666	1.40084	1.28178	1.28624	0.06804	0.06776	0.06192	0.06204
	(9.624)***	(9.573)***	(8.647)***	(8.666)***	(9.515)***	(9.466)***	(8.569)***	(8.588)***
Return on Assets	-5.67279	-5.64763	-5.71490	-5.76375	-0.27440	-0.27318	-0.27609	-0.27802
	(4.461)***	(4.445)***	(4.536)***	(4.432)***	(4.454)***	(4.438)***	(4.529)***	(4.424)***
Nonperforming Loans Ratio	-10.49586	-10.45353	-10.05614	-10.04123	-0.50770	-0.50564	-0.48582	-0.48435
	(5.752)***	(5.730)***	(5.535)***	(5.513)***	(5.727)***	(5.706)***	(5.513)***	(5.492)***
(log) Total Assets	0.25842	0.25968	0.26429	0.26447	0.01250	0.01256	0.01277	0.01276
	(11.117)***	(11.142)***	(10.745)***	(10.734)***	(10.993)***	(11.017)***	(10.632)***	(10.623)***
Equity to Assets Ratio	-4.52990	-4.51505	-4.59958	-4.64049	-0.21912	-0.21840	-0.22221	-0.22384
	(7.114)***	(7.089)***	(7.210)***	(7.254)***	(7.066)***	(7.042)***	(7.160)***	(7.204)***
Multigroup	0.55791	0.55808	0.57281	0.57188	0.03218	0.03219	0.03316	0.03302
	(7.191)***	(7.194)***	(7.329)***	(7.312)***	(6.094)***	(6.096)***	(6.185)***	(6.177)***
Unigroup	0.46745	0.46623	0.47519	0.47451	0.02173	0.02167	0.02204	0.02198
	(7.542)***	(7.520)***	(7.610)***	(7.595)***	(7.778)***	(7.755)***	(7.851)***	(7.836)***
(log) Age	-0.03647	-0.03568	-0.04179	-0.04208	-0.00176	-0.00173	-0.00202	-0.00203
	(1.571)	(1.535)	(1.720)*	(1.730)*	(1.571)	(1.535)	(1.720)*	(1.729)*
MMC Index (Cassidi)	0.81294	0.78917	0.70178	0.69723	0.03932	0.03817	0.03390	0.03363
	(7.098)***	(6.615)***	(5.734)***	(5.693)***	(7.049)***	(6.574)***	(5.707)***	(5.667)***
Herfindahl Index (Cassidi)		-0.13864	0.13300	0.13479		-0.00671	0.00643	0.00650
		(0.745)	(0.681)	(0.690)		(0.745)	(0.681)	(0.690)
Metropolitan Share			-0.06489	-0.06470			-0.00313	-0.00312
			(1.025)	(1.021)			(1.025)	(1.021)
Median Household Income			0.01677	0.01675			0.00081	0.00081
			(4.279)***	(4.271)***			(4.271)***	(4.263)***
Education (college graduates)			0.05483	0.05483			0.00265	0.00264
			(2.020)**	(2.019)**			(2.019)**	(2.018)**
Education x Internet			-0.00110	-0.00110			-0.00005	-0.00005
			(2.513)**	(2.514)**			(2.511)**	(2.512)**
Internet Use			0.02657	0.02663			0.00128	0.00128
			(3.260)***	(3.266)***			(3.255)***	(3.262)***
Constant	-6.84442	-6.81408	-8.70404	-8.39783				
	(19.791)***	(19.559)***	(14.591)***	(13.927)***				
Observations	41768	41768	41768	41768	41768	41768	41768	41768
Time dummies	No	No	No	Yes				
Log-likelihood	-8113.581	-8113.301	-8095.239	-8071.615				
Pseudo-R^2	0.054	0.054	0.056	0.059				

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

bigger loan portfolio and, in their strategy, online banking is a channel to attract more resources. Similarly, the ratio of equity to assets (a measure of leverage or capitalization) might be a proxy for conservative banking. Under this interpretation, our results would suggest that more conservative banks tend to be more reluctant to adopt online operations. An increase of 1 percentage points in the equity to assets ratio reduces the probability of adoption by about 22 basis points per quarter.

The variable that measures branching intensity (branches to assets ratio) allows us to determine whether online banking is regarded as a substitute or a complement to the physical presence. The negative and significant coefficient illustrated in table 2 suggests that physical branches and online banking are substitute strategies, as the probability of adoption declines with branching intensity.

The age of a bank is measured in log years to account for the skewness in the age distribution. This variable has a negative sign as in Sullivan and Wang (2005) although it is only marginally significant.

Regarding the strategic motivations of the adoption decision, in all the models the effect of the MMC index is positive and highly significant. That is, the adoption by more competitors in the relevant markets makes a bank more likely to adopt. This effect persists in all specifications in spite of the introduction of the Herfindahl index in models (2) to (4). The effect of the MMC index on adoption can be interpreted as follows: on average, an increase of 10 percentage points in the share of deposits controlled by a bank's competitors which have already adopted increases the probability of adoption between 34-40 basis points per quarter. To put this effect in perspective, it is important to remember that the observed probability of adoption is about 5% per quarter. The Herfindahl index, however, is not significant in any of the specifications and the sign is ambiguous.

Although variables are measured in different units, it seems that bank specific characteristics, such as the ratio of nonperforming loans, the equity to assets ratio, or the return on assets have a substantially larger economic effect on adoption than the competitive motivations measured by the MMC. Still, our results show that strategic considerations in geographically localized markets do play a significant role in the decision.

Finally, we have included demographic variables in specifications (3) and (4) to account for demand factors. Median household income, the percent of households with internet access, and the percent of population with a college degree all have the expected positive effect on adoption. The term that interacts education and internet access has a negative sign, indicating that education becomes less important for banks that operate in markets where internet is more widespread.

One possible caveat of our analysis is the existence of omitted variables correlated with the decision to adopt and with the MMC index that could bias our results. These variables could include structural characteristics of the markets where these banks operate (for example, rural versus urban areas). As a first take on this issue, we include in models (3) and (4), the proportion of bank business (in terms of deposits) conducted in metropolitan areas. This variable is not statistically significant, and its introduction does not affect the coefficient of the MMC. In the next sections we explicitly address the possible simultaneity of the MMC, and show that accounting for this fact does not change the results significantly.

Finally, an important concern is whether the results are driven by a small number of banks and, specially, banks that have been in the market for only a few years and for which financial ratios do not reflect the banks' long-run financial standing. Similar concerns might arise for large banks, that operate at a national scale, and in markets with a different competitive structure than, smaller, community banks. In order to address this issue we have also restricted the sample eliminating de-novo banks (5 years or younger) and those with assets in excess of 1 billion dollars. The sample is reduced by about two thousand observations, but the (unreported) results do not display noticeable differences with the tables presented here.

7 Adoption in Bank Groups

The results from section 6 indicate that a bank's membership to either a one-bank or a multi-bank holding company is an important determinant of the adoption decision. In this section we explore this issue further and characterize some of the differences between independent banks and those that are members of a holding company.

An initial question in this case is whether the internet-banking adoption decision is taken at the bank level (as we have assumed so far) or instead it is a holding company decision. The second case would be consistent with all banks in the holding company clustering their adoption around the same time period. In our data, this does not seem to be the case. In fact, in any period a large proportion of banks belonging to holding companies in which other member banks have previously adopted have yet to adopt.

Moreover, our data contains 121 bank holding companies in which no bank had adopted in the first period. Most of these holding companies typically include two or three banks, and their adoption is often progressive. For example, by the second period of the data, among bank holding companies in which there is adoption, in only 40% all member banks adopt simultaneously. This evidence seems to indicate that adoption is mainly an individual bank decision.

In order to examine whether the different behavior of banks that belong to holding companies is due mainly to technological reasons, we study them separately from the rest of the banks. Table 3 examines these differences. Column (1) in this table reports the logit coefficients of a model similar to model (4) in table 2, where only the dummy for the variable 'Multigroup' has been included. Columns (2) and (3) in table 3 present the logit coefficients for the samples of one-bank holding companies and independent banks vis-a-vis banks belonging to multibank holding companies. Columns (5) to (7) report the average marginal effects of these three regressions.

Our results, according to column (5) in table 3, indicate that membership in a multibank holding company increases the incentives to adopt online banking by about 1 percentage point. When we separate banks belonging to multibank holding companies from the rest, we see that most variables affect both kinds of banks in the same direction. The comparison of columns (6) and (7), however, shows that the magnitude of these effects varies depending on the kind of bank. For example, measures of profitability are more important for banks that belong to a multibank holding. The substitution between bank branches and internet banking adoption seems to be more important also for banks in multibank holding companies. In fact, except for the effects of the loans to assets ratio and the bank's size which are larger for independent banks or banks in one-bank holding companies, the marginal effects of most bank-specific measures are larger in magnitude for banks that belong to a multibank holding company.

Banks in multibank holding companies also seem to respond more to strategic considerations in their adoption decisions. The effect of the adoption of competitors, the MMC index, is about twice as large as for independent banks or one-bank holding company banks. Interestingly, banks in multibank holding companies tend to adopt earlier in more concentrated markets. That is, the Herfindahl index has a positive and statistically significant effect.

In an omitted regression that includes the interactions of the holding company dummy with the significant regressors in column (1), a log-likelihood ratio test of the joint significance of the holding company dummy and the interactions also rejects the null hypothesis of no effects of holding company membership.

Table 3 also includes an additional specification in column (4) and its corresponding marginal effects in column (8), for the sample of banks that belong to a multibank holding company. In this model a variable measuring the number of firms in the same holding that have adopted online banking has been added. This variable can be understood as a proxy for epidemic effects at the holding company level. It has a positive but not significant effect on the probability of adoption which indicates that the diffusion of this innovation is at this stage a marginal determinant of the decision to adopt.

An interpretation of these results is that banks belonging to a multibank holding company may face some advantages in the adoption of the technology. These advantages, however, are unlikely to stem from the transfer of technology, and might be partially due to different competitive motivations.

Table 3: Bank Adoption of a Transactional Website by Banks in a Holding Co.

	Logit Coefficients				Average Marginal Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Branching Intensity	-5.86987	-4.80275	-8.05011	-8.03440	-0.28358	-0.22357	-0.46628	-0.46536
	(4.967)***	(3.638)***	(2.944)***	(2.932)***	(4.949)***	(3.629)***	(2.928)***	(2.917)***
Loans to Assets Ratio	1.36162	1.55836	0.64489	0.64055	0.06578	0.07254	0.03735	0.03710
	(9.213)***	(9.487)***	(1.878)*	(1.846)*	(9.118)***	(9.360)***	(1.875)*	(1.843)*
Return on Assets	-6.13459	-5.10039	-18.18186	-18.17209	-0.29636	-0.23743	-1.05313	-1.05254
	(4.687)***	(4.027)***	(3.469)***	(3.468)***	(4.678)***	(4.021)***	(3.452)***	(3.450)***
Nonperforming Loans Ratio	-10.39073	-10.15636	-10.67227	-10.65641	-0.50198	-0.47278	-0.61816	-0.61723
	(5.711)***	(4.999)***	(2.660)***	(2.654)***	(5.688)***	(4.979)***	(2.649)***	(2.643)***
(log) Total Assets	0.27990	0.37102	0.10909	0.10858	0.01352	0.01727	0.00632	0.00629
	(11.409)***	(12.394)***	(2.176)**	(2.151)**	(11.274)***	(12.183)***	(2.172)**	(2.146)**
Equity to Assets Ratio	-5.35005	-4.13355	-6.54913	-6.55214	-0.25846	-0.19242	-0.37934	-0.37951
	(8.327)***	(5.573)***	(4.594)***	(4.595)***	(8.252)***	(5.543)***	(4.539)***	(4.540)***
(log) Age	-0.00737	-0.00189	-0.05689	-0.05707	-0.00036	-0.00009	-0.00330	-0.00331
	(0.309)	(0.072)	(0.947)	(0.950)	(0.309)	(0.072)	(0.947)	(0.949)
MMC Index (Cassidi)	0.67864	0.61617	0.91766	0.91633	0.03279	0.02868	0.05315	0.05307
	(5.567)***	(4.572)***	(3.201)***	(3.192)***	(5.542)***	(4.555)***	(3.179)***	(3.170)***
Herfindahl Index (Cassidi)	0.06055	-0.06946	0.98950	0.98828	0.00292	-0.00323	0.05731	0.05724
	(0.309)	(0.311)	(2.284)**	(2.280)**	(0.309)	(0.311)	(2.277)**	(2.273)**
Metropolitan Share	-0.11180	-0.16613	0.11198	0.11084	-0.00540	-0.00773	0.00649	0.00642
	(1.770)*	(2.371)**	(0.755)	(0.744)	(1.770)*	(2.369)**	(0.755)	(0.744)
Median Household Income	0.01614	0.01754	0.01602	0.01597	0.00078	0.00082	0.00093	0.00092
	(4.116)***	(4.049)***	(1.679)*	(1.670)*	(4.109)***	(4.040)***	(1.678)*	(1.669)*
Education (college graduates)	0.05955	0.03755	0.15834	0.15811	0.00288	0.00175	0.00917	0.00916
	(2.191)**	(1.246)	(2.427)**	(2.422)**	(2.190)**	(1.246)	(2.419)**	(2.414)**
Education x Internet	-0.00117	-0.00085	-0.00273	-0.00272	-0.00006	-0.00004	-0.00016	-0.00016
	(2.663)***	(1.739)*	(2.564)**	(2.555)**	(2.661)***	(1.739)*	(2.554)**	(2.545)**
Internet Use	0.02774	0.02358	0.05107	0.05099	0.00134	0.00110	0.00296	0.00295
	(3.401)***	(2.625)***	(2.575)**	(2.569)**	(3.396)***	(2.622)***	(2.565)**	(2.559)**
Multi-Bank Bank Holding	0.20756				0.01067			
	(3.443)***				(3.241)***			
Banks in the holding that have adopted				0.00083				0.00005
				(0.087)				(0.087)
Constant	-8.31261	-9.41992	-6.66734	-6.65502				
	(13.793)***	(13.576)***	(4.776)***	(4.744)***				
Observations	41768	35859	5909	5909	41768	35859	5909	5909
Time dummies	Yes	Yes	Yes	Yes				
Log-likelihood	-8102.472	-6738.144	-1317.801	-1317.797				
Pseudo-R^2	0.056	0.060	0.062	0.062				

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

8 Robustness Analysis

In this section we perform several sensitivity checks to study the robustness of the results to changes in the geographic definitions used for our measure of multimarket contact. We also study the potential existence of omitted variables in our benchmark specification. In an earlier working paper version we show that the results are preserved if we alternatively use the mere existence of a corporate website as a measure of internet presence, regardless of whether this website allows customers to perform transactions online.

8.1 Changes in the Geographical Definition

In this section we consider a definition of bank markets that is more familiar in the literature. In particular, we distinguish between urban and rural areas. For urban areas we use the so-called *Core Based Statistical Areas* (CBSA). For rural areas we assign the county as the market. CBSAs are used by the U.S. Census Bureau to replace the definitions of metropolitan areas defined in 1990 and they are organized around urban centers of at least 10,000 people. With this new definition we recompute the Multimarket contact index and the Herfindahl-Hirschman index. We report the results in tables 4.

Our results are in line with those of the previous sections. The effects of the different control variables maintain the same sign and comparable magnitudes. Some variables lose statistical significance, while others that were not statistically significant become so with the inclusion of these additional cities. It is interesting to notice that the MMC index remains statistically significant in all specifications and its average marginal effect is very similar to the one obtained in the baseline case.

Finally, previous versions of the paper considered alternative definitions of geographical markets. We entertained two possibilities; the usage of the zip code or the county as a relevant market. The results were qualitatively unchanged and for brevity they have been omitted in this version of the paper.

8.2 Omitted Variables

Our results relating competition to the adoption of a transactional website hinge on the idea that no relevant variables for the adoption decision (and correlated to the MMC) have been omitted in the regression. If such variables exist our results are likely to be biased.

Our benchmark model tries to control for the most obvious candidate for these omitted variables, namely market characteristics that might affect both the adoption of competitors and the

Table 4: Bank Adoption of a Transactional Website (County/CBSA Level)

	Logit Coefficients				Average Marginal Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
time	0.01758	0.01804	0.02026		0.00085	0.00087	0.00098	
	(0.814)	(0.836)	(0.937)		(0.814)	(0.836)	(0.937)	
$time^2$	0.00066	0.00065	0.00065		0.00003	0.00003	0.00003	
	(0.485)	(0.476)	(0.476)		(0.485)	(0.476)	(0.476)	
Branching Intensity	-5.57788	-5.55260	-5.60502	-5.62194	-0.26975	-0.26852	-0.27075	-0.27114
	(4.756)***	(4.735)***	(4.744)***	(4.753)***	(4.740)***	(4.719)***	(4.728)***	(4.737)***
Loans to Assets Ratio	1.41096	1.40736	1.28993	1.29436	0.06823	0.06806	0.06231	0.06243
	(9.646)***	(9.620)***	(8.693)***	(8.712)***	(9.537)***	(9.512)***	(8.613)***	(8.633)***
Return on Assets	-5.61794	-5.57342	-5.68206	-5.73114	-0.27169	-0.26953	-0.27447	-0.27641
	(4.433)***	(4.406)***	(4.505)***	(4.400)***	(4.426)***	(4.399)***	(4.498)***	(4.393)***
Nonperforming Loans Ratio	-10.52768	-10.45369	-10.07255	-10.05821	-0.50912	-0.50553	-0.48655	-0.48510
	(5.777)***	(5.736)***	(5.544)***	(5.523)***	(5.753)***	(5.712)***	(5.522)***	(5.501)***
(log) Total Assets	0.25511	0.25602	0.26531	0.26542	0.01234	0.01238	0.01282	0.01280
	(10.955)***	(10.983)***	(10.783)***	(10.769)***	(10.836)***	(10.863)***	(10.669)***	(10.657)***
Equity to Assets Ratio	-4.54177	-4.51919	-4.60201	-4.64344	-0.21964	-0.21854	-0.22230	-0.22395
	(7.129)***	(7.094)***	(7.199)***	(7.243)***	(7.081)***	(7.046)***	(7.149)***	(7.194)***
Multigroup	0.57216	0.57383	0.57911	0.57820	0.03315	0.03327	0.03359	0.03345
	(7.368)***	(7.388)***	(7.408)***	(7.392)***	(6.218)***	(6.233)***	(6.242)***	(6.233)***
Unigroup	0.46796	0.46813	0.47014	0.46955	0.02174	0.02175	0.02181	0.02175
	(7.548)***	(7.552)***	(7.531)***	(7.518)***	(7.786)***	(7.789)***	(7.771)***	(7.757)***
(log) Age	-0.03352	-0.03183	-0.04179	-0.04208	-0.00162	-0.00154	-0.00202	-0.00203
	(1.444)	(1.367)	(1.723)*	(1.733)*	(1.444)	(1.367)	(1.722)*	(1.732)*
MMC Index (County)	0.83198	0.80308	0.73802	0.73447	0.04023	0.03884	0.03565	0.03542
	(7.794)***	(7.170)***	(6.361)***	(6.326)***	(7.729)***	(7.119)***	(6.325)***	(6.290)***
Herfindahl Index (County)		-0.15994	0.09006	0.09605		-0.00773	0.00435	0.00463
		(0.886)	(0.449)	(0.479)		(0.886)	(0.449)	(0.479)
Metropolitan Share			-0.10550	-0.10468			-0.00510	-0.00505
			(1.604)	(1.590)			(1.603)	(1.590)
Median Household Income			0.01666	0.01665			0.00080	0.00080
			(4.234)***	(4.227)***			(4.226)***	(4.219)***
Education (college graduates)			0.05461	0.05472			0.00264	0.00264
			(2.010)**	(2.013)**			(2.010)**	(2.013)**
Education x Internet			-0.00108	-0.00108			-0.00005	-0.00005
			(2.458)**	(2.463)**			(2.456)**	(2.461)**
Internet Use			0.02497	0.02508			0.00121	0.00121
			(3.052)***	(3.064)***			(3.048)***	(3.060)***
Constant	-6.83772	-6.80091	-8.64343	-8.34082				
	(19.827)***	(19.571)***	(14.438)***	(13.793)***				
Observations	41768	41768	41768	41768	41768	41768	41768	41768
Time dummies	No	No	No	Yes				
Log-likelihood	-8107.605	-8107.208	-8091.108	-8067.492				
Pseudo-R^2	0.055	0.055	0.057	0.060				

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

bank's own adoption. The fact that variables such as the share of deposits that correspond to branches in metropolitan areas (as a measure of clientele in rural areas) do not affect substantially the results in table 2 suggests that this might not be an important problem.

In this subsection we take a different approach. One of the usual remedies to control for the existence of omitted variables is to instrument the MMC index with a variable that although correlated with the adoption of competitors it does not directly affect the bank's adoption in any other way. In particular, we consider as an instrument the percentage of competitor banks that belong to a holding. As we have earlier shown, membership in a holding company is positively correlated with the bank's own adoption, and hence this variable should be positively correlated with the MMC index. However, there is no reason to expect that this variable affects the adoption decision beyond the channel considered. Our instrument has a correlation of about 30% with the MMC.

We estimate this model using a two-stage logit, modifying the probit procedure outlined in Wooldridge (2001) (pg. 472), which in our case yields consistent estimators albeit under stronger distributional assumptions. In particular, in the first stage we compute the residuals from regressing the MMC on the exogenous variables of our model together with the instrument described earlier. The standardized residuals of this first stage are introduced in the logit estimation as an additional regressor. Table 9 in the appendix and table 5 report the first and second stage respectively.[17]

The results in these tables do not present significant changes with respect to our benchmark specification. The magnitude of the MMCs effect is similar and statistically significant. It is also important to notice that the residual from the first stage is not significant in the logit specification, reinforcing the idea that omitted variables should not be biasing the results.

9 Concluding Remarks

In this paper we have analyzed the determinants of the adoption of online banking operations among U.S. banks. In contrast with the existing literature, we regard the adoption decision as a strategic dynamic choice. For this reason we use a recently available panel dataset that allows us to track adoption decisions over time that we estimate using a discrete hazard model.

One of the contributions of this paper has been to study the effects of competition in a context where firms interact in a geographical environment. The adoption of online banking occurs

[17] The t-statistics reported for the second stage are obtained using a bootstrap procedure. For the estimation of the average marginal effects we follow Wooldridge (2001) (pg. 475) and for the calculation of the standard errors we rely on the delta method using numerical derivatives. The significance is reported using the theoretical distribution, although the simulated one yields to similar results.

Table 5: Bank Adoption of a Transactional Website (2s-logit).

	Logit Coefficients				Average Marginal Effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Residuals	-0.1279	-0.1346	-0.0746	-0.0734				
	(1.425)	(1.466)	(0.785)	(0.772)				
time	0.0095	0.0090	0.0146		0.0005	0.0004	0.0007	
	(0.438)	(0.412)	(0.668)		(0.439)	(0.412)	(0.668)	
time^2	0.0008	0.0008	0.0008		0.0000	0.0000	0.0000	
	(0.597)	(0.598)	(0.582)		(0.598)	(0.598)	(0.582)	
MMC Index (Cassidi)	1.3479	1.3849	1.0355	1.0256	0.0669	0.0688	0.0507	0.0501
	(3.586)***	(3.438)***	(2.426)**	(2.402)**	(3.424)***	(3.287)***	(2.370)**	(2.346)**
Branching Intensity	-5.6637	-5.6650	-5.6339	-5.6515	-0.2811	-0.2814	-0.2759	-0.2762
	(4.322)***	(4.325)***	(4.263)***	(4.264)***	(4.297)***	(4.299)***	(4.253)***	(4.243)***
Loans to Assets Ratio	1.3976	1.4100	1.2997	1.3039	0.0694	0.0700	0.0636	0.0637
	(10.054)***	(10.284)***	(9.237)***	(9.216)***	(10.092)***	(10.190)***	(9.134)***	(9.018)***
Return on Assets	-5.4213	-5.3974	-5.6331	-5.6816	-0.2691	-0.2681	-0.2758	-0.2777
	(2.817)***	(2.805)***	(3.041)***	(2.936)***	(2.817)***	(2.804)***	(3.037)***	(2.930)***
Nonperforming Loans	-10.1860	-10.1314	-9.8054	-9.7874	-0.5056	-0.5032	-0.4802	-0.4784
	(5.282)***	(5.271)***	(5.159)***	(5.133)***	(5.263)***	(5.252)***	(5.147)***	(5.103)***
(log) Total Assets	0.2394	0.2364	0.2552	0.2556	0.0119	0.0117	0.0125	0.0125
	(9.700)***	(9.066)***	(9.778)***	(9.788)***	(10.083)***	(9.509)***	(9.948)***	(9.847)***
Equity to Assets Ratio	-4.4848	-4.4695	-4.5598	-4.6005	-0.2226	-0.2220	-0.2233	-0.2249
	(6.113)***	(6.094)***	(6.161)***	(6.185)***	(6.064)***	(6.044)***	(6.140)***	(6.133)***
Multigroup	0.5626	0.5644	0.5689	0.5679	0.0279	0.0280	0.0279	0.0278
	(7.004)***	(7.029)***	(6.988)***	(6.972)***	(6.862)***	(6.882)***	(6.891)***	(6.833)***
Unigroup	0.4749	0.4772	0.4785	0.4779	0.0236	0.0237	0.0234	0.0234
	(7.610)***	(7.635)***	(7.599)***	(7.569)***	(7.491)***	(7.488)***	(7.520)***	(7.440)***
(log) Age	-0.0159	-0.0157	-0.0345	-0.0349	-0.0008	-0.0008	-0.0017	-0.0017
	(0.556)	(0.555)	(1.247)	(1.255)	(0.558)	(0.557)	(1.253)	(1.260)
Herfindahl Index (Cassidi)		0.1769	0.2712	0.2708		0.0088	0.0133	0.0132
		(0.604)	(1.030)	(1.027)		(0.600)	(1.023)	(1.020)
Metropolitan share			-0.0867	-0.0862			-0.0042	-0.0042
			(1.295)	(1.288)			(1.288)	(1.281)
Median Household Income			0.0161	0.0161			0.0008	0.0008
			(4.015)***	(4.006)***			(4.034)***	(4.015)***
Education (college graduates)			0.0466	0.0466			0.0023	0.0023
			(1.546)	(1.550)			(1.550)	(1.553)
Education x Internet			-0.0010	-0.0010			-0.0000	-0.0000
			(1.992)**	(1.999)**			(1.998)**	(2.005)**
Internet Use			0.0241	0.0242			0.0012	0.0012
			(2.744)***	(2.753)***			(2.761)***	(2.768)***
Constant	-7.1038	-7.1453	-8.7352	-8.4833				
	(18.425)***	(17.582)***	(14.313)***	(13.392)***				
Observations	41421	41421	41421	41421				
Time dummies	No	No	No	Yes				

Absolute value of standardized coefficients in parentheses (constructed with bootstrapped standard errors).
* significant at 10%; ** significant at 5%; *** significant at 1% (relative to a standard normal).

simultaneously across all markets where the bank operates. By controlling for the level of concentration in each market we isolate the strategic component of the adoption decision and find it to be significant in a variety of specifications.

We also find that bank-specific characteristics, such standard measures of financial health and bank size, are the main determinants in the adoption decision. Our results also indicate that bank membership to a holding company is an important factor in the speed of adoption. However, the fact that banks in most holding companies do not adopt simultaneously indicates that the adoption decision is taken at the bank level.

The paper also sheds some light on the role of online banking as a part of a bank's strategy. We show that these institutions regard it as an alternative to opening new branches.

In terms of the competitive effects that condition the adoption decision described by Karshenas and Stoneman (1993), we find that stock effects are a sensible explanation for our results. The positive effect of the competitor's adoption in the adoption decision indicates that these decisions are strategic complements. This positive effect also suggests that order effects are unlikely, because the preemptive adoption of competitors would entail a negative effect on a bank's decision. Inasmuch as adoption is unrelated to the adoption of other banks in the same group, we find evidence against epidemic effect.

This paper is a first approach to the study of these strategic considerations. Further research in this area might pursue the specification of a structural dynamic model of adoption. Although at a cost of higher technical complexity, structural estimation could help quantifying the effect of each motivation.

Finally, the setup in this paper can be applied to other contexts. Many adoption decisions are irreversible and implemented in several markets at the same time. An example could be the adoption of new inventory systems for retailers that operate in several markets, to the extent that competitors partially overlap across different markets.

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A Data Appendix

Table 6: Variable Definitions and Sources

Variable	Variable Code
Summary of Deposits	
Branch Count	Authors' calculations
Branch Deposits	DEPSUMBR
Metropolitan Branch Flag	CBSA_METROB
Zip Code Branch	ZIPBR
State Code Branch	STNUMBR
Multi-Bank Holding Company Flag	HCTMULT
One Bank Holding Company Flag	HCTONE
No Bank Holding Company Flag	HCTNONE
Call Reports	
Opening Date	rssd9950
Total Deposits	rcfd2200
Non-accrual or 90 days Past-due Loans	rcfd1403 + rcfd1407
Total Loans and Leases	rcfd2122
Total Assets	rcfd2170
Net Income (numerator of ROA)	riad4340
Quarterly Avg. Assets (denominator of ROA)	rcfd3368
Total Equity	rcfd3210
Transactional Website	rcfd4088
Corporate Website	text4087
U.S. Census Bureau	
Population	2000 Census SF3 Long Form
Median Household Income	2000 Census SF3 Long Form
People aged 18 to 64 Years Who Have Completed a Bachelor's Degree or Higher	2000 Census SF3 Long Form
Current Population Survey	
Percent of Households with Internet Access	2003 Internet Usage Supplement

Table 7: Summary Statistics as of March 2003

Variable	stat.	Adoption = 0	Adoption = 1	Total
Number of banks		4105	3683	7788
Age (years)	Mean	67.2	62.0	64.7
	Med.	79.2	69.2	73.2
MMC Index (Cassidi)	Mean	0.7143	0.8177	0.7632
	Med.	0.8026	0.8904	0.8608
Herfindahl Index (Cassidi)	Mean	0.2077	0.1913	0.2000
	Med.	0.1701	0.1670	0.1684
Number of branches	Mean	2.8	15.8	8.9
	Med.	2.0	4.0	2.0
Branching Intensity	Mean	0.0406	0.0263	0.0339
	Med.	0.0330	0.0229	0.0272
Number of competitors	Mean	27.1	35.2	31.0
	Med.	12.0	17.4	14.0
Number of Cassidi markets codes	Mean	1.4	3.2	2.3
	Med.	1.0	1.0	1.0
Multi-bank holding	Mean	0.2	0.3	0.2
	Med.	0.0	0.0	0.0
One-bank holding	Mean	0.6	0.6	0.6
	Med.	1.0	1.0	1.0
Total Assets (mill.)	Mean	188.7	1709.1	907.7
	Med.	58.2	169.2	93.9
Equity to Asset Ratio	Mean	0.1213	0.1015	0.1120
	Med.	0.1028	0.0908	0.0962
Loan to Asset Ratio	Mean	0.5809	0.6429	0.6102
	Med.	0.5963	0.6652	0.6323
Non-Performing Loans	Mean	0.0138	0.0099	0.0119
	Med.	0.0074	0.0062	0.0067
Return on Assets	Mean	0.0096	0.0111	0.0103
	Med.	0.0107	0.0114	0.0110
Median Household Income (thous.)	Mean	36.9	40.9	38.8
	Med.	35.5	39.4	37.2
Metropolitan Share	Mean	0.4266	0.6208	0.5184
	Med.	0.0000	0.9750	0.6361
Education (college graduates)	Mean	18.8	22.9	20.8
	Med.	16.3	21.1	18.2
Internet use (%)	Mean	58.0	60.5	59.2
	Med.	58.3	60.8	59.5

Note: Mean and median statistics are taken at the bank level.

Table 8: Correlation Table.

Variables	MMC Index (Cassidi)	Herfindahl Index (Cassidi)	Branching Intensity	Loans to Assets Ratio	Return on Assets	Nonperforming Loans Ratio	(log) Total Assets	Equity to Assets Ratio	Multigroup	Unigroup	(log) Age	Metropolitan Share	Median Household Income	Education (college graduates)	Internet Use
MMC Index (Cassidi)	1.000														
Herfindahl Index (Cassidi)	-0.394*	1.000													
Branching Intensity	-0.057*	-0.016*	1.000												
Loans to Assets Ratio	0.067*	-0.094*	-0.107*	1.000											
Return on Assets	0.003	0.009	-0.060*	-0.038*	1.000										
Nonperforming Loans Ratio	-0.047*	0.029*	0.014*	-0.077*	-0.080*	1.000									
(log) Total Assets	0.159*	0.001	-0.589*	0.159*	0.040*	-0.022*	1.000								
Equity to Assets Ratio	0.002	0.028*	0.218*	-0.351*	0.252*	0.074*	-0.160*	1.000							
Multigroup	-0.011*	0.013*	0.007	0.024*	0.016*	0.025*	0.046*	0.052*	1.000						
Unigroup	-0.026*	-0.031*	-0.075*	0.092*	-0.022*	-0.038*	0.071*	-0.179*	-0.486*	1.000					
(log) Age	-0.184*	0.087*	0.097*	-0.149*	0.017*	0.044*	-0.167*	-0.097*	-0.015*	0.146*	1.000				
Metropolitan Share	0.323*	-0.274*	-0.110*	0.043*	0.004	0.006	0.261*	0.081*	-0.011*	-0.096*	-0.338*	1.000			
Median Household Income	0.306*	-0.309*	-0.086*	0.106*	-0.006	-0.028*	0.200*	0.095*	-0.027*	-0.041*	-0.301*	0.570*	1.000		
Education (college graduates)	0.257*	-0.211*	-0.078*	0.051*	-0.011*	0.027*	0.234*	0.119*	-0.007	-0.059*	-0.346*	0.509*	0.690*	1.000	
Internet Use	0.267*	-0.315*	0.024*	0.144*	-0.004	-0.021*	0.058*	0.055*	0.002	-0.021*	-0.130*	0.432*	0.535*	0.450*	1.000

* indicates significant at 10%.

Table 9: First Stage Regression over MMC.

	(1)	(2)	(3)	(4)
Perc. of Competitors that belong to a holding	0.29371	0.27710	0.27381	0.27399
	(49.711)***	(49.329)***	(49.318)***	(49.325)***
time	0.01023	0.01081	0.01117	
	(9.538)***	(10.607)***	(11.251)***	
time^2	0.00006	0.00003	0.00003	
	(0.814)	(0.505)	(0.445)	
Branching Intensity	0.14141	0.14881	0.05183	0.05184
	(3.193)***	(3.538)***	(1.261)	(1.261)
Loans to Assets Ratio	0.02343	-0.01041	-0.02690	-0.02686
	(3.333)***	(1.555)	(4.066)***	(4.057)***
Return on Assets	-0.49574	-0.43079	-0.26228	-0.26372
	(7.060)***	(6.458)***	(4.028)***	(4.049)***
Nonperforming Loans Ratio	-0.19699	-0.17311	-0.21150	-0.21228
	(4.185)***	(3.872)***	(4.843)***	(4.860)***
(log) Total Assets	0.03484	0.03892	0.02370	0.02369
	(24.789)***	(29.124)***	(17.423)***	(17.417)***
Equity to Assets Ratio	-0.06866	-0.05045	-0.13088	-0.13096
	(3.293)***	(2.547)**	(6.717)***	(6.719)***
Multigroup	-0.03542	-0.03441	-0.02160	-0.02159
	(9.515)***	(9.730)***	(6.244)***	(6.242)***
Unigroup	-0.02039	-0.02430	-0.01433	-0.01434
	(7.537)***	(9.458)***	(5.692)***	(5.696)***
(log) Age	-0.03365	-0.02889	-0.01476	-0.01475
	(27.636)***	(24.935)***	(12.339)***	(12.329)***
Herfindahl Index (Cassidi)		-0.56843	-0.41006	-0.40991
		(67.017)***	(45.511)***	(45.487)***
Metropolitan Share			0.07014	0.07016
			(24.146)***	(24.151)***
Median Household Income			0.00165	0.00165
			(8.545)***	(8.542)***
Education (college graduates)			0.01371	0.01372
			(11.020)***	(11.025)***
Education x Internet			-0.00020	-0.00020
			(9.991)***	(9.994)***
Internet Use			0.00448	0.00449
			(12.463)***	(12.464)***
Constant	0.37738	0.45338	0.16782	0.34364
	(20.173)***	(25.465)***	(6.064)***	(12.302)***
Observations	41421	41421	41421	41421
R^2	0.136	0.221	0.260	0.260

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%